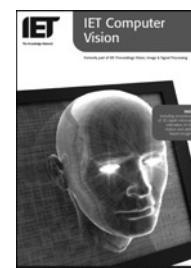


Published in IET Computer Vision  
 Received on 30th November 2007  
 Revised on 16th April 2008  
 doi: 10.1049/iet-cvi:20070069

In Special Issue on Visual Information Engineering



ISSN 1751-9632

# Task-related population characteristics in handwriting analysis

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**Abstract:** An analysis of features extracted from handwriting samples according to writer demographics and writing task characteristics is presented. The individual demographics studied here include age, gender and handedness, while the handwriting tasks considered include writing the individual signature, form-filling, cheque-completion and constructing free-form written text. By analysing different features of handwriting, the authors establish a link between a writer's individual characteristics including demographic properties, the handwriting task being attempted and quantifiable features of handwriting such as pen velocity, acceleration and slant. Additionally, imitated or 'forged' handwriting is also analysed on exactly the same basis. The analysis is performed on a newly collected database of handwriting samples collected from a population of 150 writers, and which can be utilised in both forensic document inspection and automatic handwriting analysis research. All handwriting samples, including forgery attempts, were recorded both temporally as a series of pen positional coordinates and scanned at a resolution of 600 dpi to enable both dynamic and static processing.

## 1 Introduction

In recent years there has been a renewed interest in the way in which forensic document analysts utilise their expertise, principally because of the perceived lack of a quantitative underpinning of the procedures adopted. The practice of forensic document examination is based on long-established principles originally defined by, for example, Conway [1], Harrison [2], Hilton [3] and Osborn [4], but there has been an increasing desire to support the high level of skill which document examiners possess with a greater degree of more objective scientific and experimental validation. In particular, many attempts have been made to analyse the process of handwriting imitation/forgery. Despite this, the field of automatic handwriting analysis does not yet offer comprehensive insights into the problem. On the contrary, much of the reported research concentrates on analysing forged writing when only the forged sample(s) exist(s) and in the absence of the genuine writing of the forger. However, automated handwriting analysis has demonstrated how dynamic (constructional) features, which describe valuable writer-specific characteristics, can help greatly in discriminating between

writers [5], although not all practical situations reveal this sort of information directly.

Numerous studies have investigated computer-based assessment of text for writer identification analysing the 'static' features conventionally assessed by document examiners, but also extracting and examining novel 'dynamic' constructional features from time-sequenced data and inferring dynamic properties from the static image, providing pointers which can be useful in a wider range of situations. Franke and Grube [6], for example, have proposed a method to establish pseudo-dynamic data by assessing the ink intensity variations of the writing trace. In fact, the method adopted was derived from forensic experience and improved by utilising digital image processing algorithms. A further study [7] examined the value of using information relating pen to pressure for writer identification. Within a group of 24 subjects, the authors failed to identify any distinction in pressure between normal and simulated handwriting. Another study on the effects of handwriting pressure on writer identification was presented by Estabrooks [8]. In this study, the author describes a procedure to measure relative pen pressure from the static

image with the use of a confocal laser scanning microscope. The author claims that 'relative depth values of simulated and traced signatures are similarly measured and are generally found to be clearly distinguishable from genuine signatures'. Additionally, Spagnolo *et al.* [9] presented a holographic method of identifying a writer from the pen pressure exerted on the paper in the process of writing. This technique constructs a three-dimensional image from the interference patterns of two laser beams used to scan an object – in this case, a sample of handwriting. The resulting image can be interpreted as a series of troughs of varying depths denoting the pressure of the pen strokes used to make them.

The effects of writing speed on signature simulation were investigated in [10, 11]. In both studies, 12 subjects were asked to trace and copy an historical signature. Capturing responses on a graphics tablet, kinematic analysis was performed on the speed and pressure of writing. The variability of samples was also measured. It was found that pen pressure varies more with speed during free non-traced simulations. Writing speed was established to be an important factor influencing line quality and spatial correspondence during signature simulation.

Other studies assessing aspects of automatic writer identification include the work of Wirotius *et al.* [12] who considered the distribution of the pixel levels within an ink line and identified a link to pressure and writing speed. Schomaker *et al.* [13] proposed the use of an edge-based directional probability distribution as a feature in writer identification to complement a number of non-angular features. An interesting pattern matching method for writer identification was proposed by Ueda [14]. This method was independent of stroke width, resulting in improved identification results. Another interesting approach for writer identification employs fractal construction of a reference base as a feature [15]. This feature was found to be closely related to writing style. Bensefia *et al.* [16] exploited graphemes using an information retrieval paradigm to describe and compare a questioned handwritten sample to each sample of handwriting in a database, whereas, in Wang *et al.* [17], directional element features and linear transforms are used for effective writer identification. In Schomaker *et al.* [18], an automatic writer identification method using fragmented connected-component contours is introduced, and Bulacu *et al.* [19] evaluate the performance of edge-based directional probability distributions as features in writer identification comparing to other non-angular features. Said *et al.* [20] performed texture analysis by means of a multi-channel Gabor filtering technique, and a multi-expert signature verification method is described by Bovino *et al.* [21] using a stroke-oriented description of signatures. Matsuura and Thumwarin [22] transform the time sequences of displacement and its directional change using the wavelet transform. A wavelet-based generalised Gaussian density method for offline writer identification was proposed by He

*et al.* [23], whereas Schmidt and Hunermann [24] use the features extracted from an ellipse obtained from processing the velocity–space diagram and extract a series of features including: position of the ellipse, angle of the ellipse's main axes to x-axes and the radii of the ellipse.

The fields of forensic document examination and automatic writer identification would mutually benefit greatly from a sharing of a common knowledge base. Automatic writer identification can offer technologically advanced methods to facilitate, enhance and validate the work of a document examiner. On the other hand, the accumulated knowledge gained by document examiners over more than 100 years is extremely valuable for the creation of new engineering solutions for the writer identification problem. Furthermore, it is also clear that in forensic handwriting analysis, several important factors can influence the behavioural patterns which underlie the handwriting process – for example, the occupational characteristics of the writer, national or ethnic origin, even the task context in which the writing is executed – and a better understanding of such factors and their influence could be important and valuable in seeking greater integration across the boundaries of the forensic/engineering communities. This paper represents a step in this direction and, in particular, seeks to explore the nature, variability and discriminatory power of a range of commonly extracted features of handwriting in relation to some of the factors which characterise the writer.

The forensic document analysis community currently do not employ most of the dynamic features which have been shown to be very successful in engineering applications of handwriting analysis. We will explore some of the potential benefits associated with dynamic analysis and, in particular, how these features vary when writers perform different types of writing tasks. However, it must also be recognised that it is precisely these dynamic features which are not generally available in most forensic analysis tasks. This, then, points to the possible benefits of developing a strategy based on the better exploitation and effective deployment of static handwriting features, or the increasing refinement of techniques to predict 'pseudo-dynamic' features from static measurements. Similarly, automatic handwriting analysis specialists can benefit from a better understanding of how the constraints imposed by different task environments and objectives can influence the way in which handwriting tasks are executed, particularly, in relation to the effect these have on the analytical power of different extractable features.

Thus, in the study reported here, we wish to investigate the stability and discriminatory capability of a number of writing features commonly extracted from (generally small-scale) writing samples. In particular, we wish to analyse the difference in the analytical power of features across a range of different writing tasks, across different population demographics and across subjects, both as they produce

their own handwriting and while imitating (as perhaps a criminal forger might attempt) handwriting samples from other writers. The paper is organised in three further sections, describing the compilation of a database of widely varying handwriting samples, presentation of an analysis of the data and, finally, a discussion of some conclusions which can be drawn from the work.

## 2 Database

To support our assessment of feature-based writing characteristics in different writing tasks and populations, a database of handwriting samples from 150 participants was collected. Table 1 shows the participants' distribution by age, gender, handedness and writing language.

The data collection was performed in two separate sessions. In Session 1, participants were asked to adopt their normal handwriting to complete four different target writing scenarios: (i) constrained form filling, (ii) bank cheque completion (numeric amount in words and numerals and signature), (iii) free-form signature production and (iv) cursive and block handwriting (copying a passage of text). In Session 2, subjects were asked to copy the signature and handwriting of one of ten pre-collected target subjects. Prior to formally copying the handwriting, the test subject had an unlimited amount of time to practice the task on a designated practice sheet. As with the target tasks themselves, the data generated in the practice session were captured using a graphics tablet to enable further dynamic analysis. Each test subject was then asked to reproduce signatures and the target cheque-based information with the reference handwriting model visible at all times.

Each writing sample within each session was recorded digitally at 100 Hz using a Wacom Intuos 2 Tablet and a three-axis force sensitive pen with captured constructional data stored on a connected computer. For each sample point, the tablet returned  $x$  and  $y$  positional data, downwards force on to the tablet surface, pen tilt data and

button status (indicating contact with tablet surface). These data were stored along with a timestamp to enable the extraction of dynamic/constructional features alongside static measurements relating to the outcome of the handwriting process (i.e. the completed image). Additionally, each writing sample was then scanned at a resolution of 600 dpi, to enable analysis using both human-mediated (as in forensic analysis) and (static) automatic handwriting analysis techniques to be applied.

The collected database contains:

1. genuine samples from four target scenarios in Session 1 – 150 samples of handwriting within the physical constraints imposed within a form-filling scenario, 2250 samples of individual handwritten signatures, 90 samples of bank cheque completion and 300 samples of a short written paragraph in both normal cursive script and block capital handwriting (hand-printing).
2. imitated (forged) samples (hereafter referred to simply as the forged samples) from Session 2 – 420 practice sheets for forged signatures, 1260 forged signatures, 140 practice sheets for forged cheques and 420 forged cheques.

## 3 Data analysis

A feature 'pool' was defined (Table 2), comprising some of the most widely used static and dynamic features typically reported in the literature of automatic handwriting analysis [25]. Features such as velocities, pen pressures, tilt altitudes and azimuths, handwriting dimensions and shape-descriptive moments are calculated directly from the data available from the digital tablet. The feature vector overall consists of 35 features, representing both the process of writing (dynamics – features 1–19, 23–31) and the shape of the handwriting sample (static – features 20–22, 32–35) (Table 2). Within the database, the extent of handwritten samples can vary from a single handwritten word to an entire page of handwritten text. Therefore features are extracted globally

**Table 1** Participant distribution

Age groups	18–29	30–40	40–50	50–60	60–70	over 70
	55%	10.50%	6%	10.50%	11.30%	6.70%
Gender	male	female				
	39.90%	60.10%				
Hand	right	left				
	91%	9%				
Writing language	English	Western*	Non-Western			
	81%	8%	11%			

\*Specifically, Western, but non-English

**Table 2** Feature vector and units

Feature ID	Feature	Feature type	Units
1	average horizontal velocity	dynamic	$10^{-2}$ mm/ms
2	maximum horizontal velocity		
3	average vertical velocity		
4	maximum vertical velocity		
5	average Cartesian velocity		
6	maximum Cartesian velocity		
7	maximum horizontal velocity–minimum horizontal velocity		
8	maximum vertical velocity–minimum vertical velocity		
9	maximum horizontal velocity–average horizontal velocity		
10	maximum vertical velocity–average vertical velocity		
11	maximum horizontal velocity–maximum vertical velocity		
12	average pen pressure		Levels 0 – 1023
13	maximum pen pressure		
14	average altitude		$10^{-1}$ degrees
15	maximum altitude		
16	average azimuth		
17	maximum azimuth		
18	number of pen-ups		pen-up count
19	pen-down to pen-up ratio		dimensionless
20	slant	static	$10^{-1}$ degrees
21	width		$10^{-2}$ mm
22	height		
23	writing duration	dynamic	ms
24	average pen-pressure acceleration		$10^{-2}$ mm/ms <sup>2</sup>
25	maximum pen-pressure acceleration		
26	average azimuth acceleration		
27	maximum azimuth acceleration		
28	positive duration of horizontal velocity		ms
29	negative duration of horizontal velocity		
30	positive duration of vertical velocity		
31	negative duration of vertical velocity		
32	orientation	static	dimensionless
33	inertial ratio		
34	aspect ratio		
35	spread		

across each handwritten sample. The number of dynamic features exceeds the number of static features for the purposes of demonstrating the advantages of using the dynamic information extracted from handwritten documents.

Most of the features are calculated directly from the digitiser's data channels and are very straightforward in their definition, but some features, such as feature 20 and features 32–35 benefit from further explanation.

Slant (Feature ID 20) is calculated by correcting the baseline to horizontal, extracting the downwards pen strokes from the hand-drawn sample, eliminating the initial and final strokes (being inconsistent with the main slant), and calculating the average angle between the downstrokes and a word baseline. Down strokes are used for slant measurement because they are less prone to variation than the upstrokes [26]. This may be due to the fact that upstrokes are often connecting individual letters. This is also confirmed by visual observation, as reported in other studies, for example [27].

Features 32–35 (equations (2) to (5), respectively) are calculated from central moments (1). Moments have been used extensively in image processing and pattern analysis and are widely used in handwriting recognition [28, 29] and, in writer identification [30]. The central moment of the  $(p, q)$ th order of handwriting samples of  $N$  sample points comprising  $x$  and  $y$  pen-coordinate positions are calculated as

$$\mu_{pq} = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^p (y_i - \bar{y})^q \quad (1)$$

where  $p, q = 0, 1, 2, \dots, \infty$ . The inertial moments provide important shape information; they can be extracted from the second- and third-order moments [31].

### 3.1 Analysis of feature combination for different handwriting patterns

In an initial investigation, the differences between the four different target writing scenarios across the entire set of features were analysed. Each feature was analysed separately to identify a subset that can be used to discriminate between the writers' personal characteristics; such information is particularly important for the field of forensic handwriting analysis as well as for automatic handwriting analysis. As different features describe different properties of the handwriting process (and hence have different data ranges), they are not always directly comparable. It is therefore necessary to normalise each feature prior to combining them into the feature vectors used for subsequent processing. Linear normalisation was performed by scaling and translating feature values between values of 0 and 1. Fig. 1 shows the mean and the standard deviation curve for the normalised features based on the

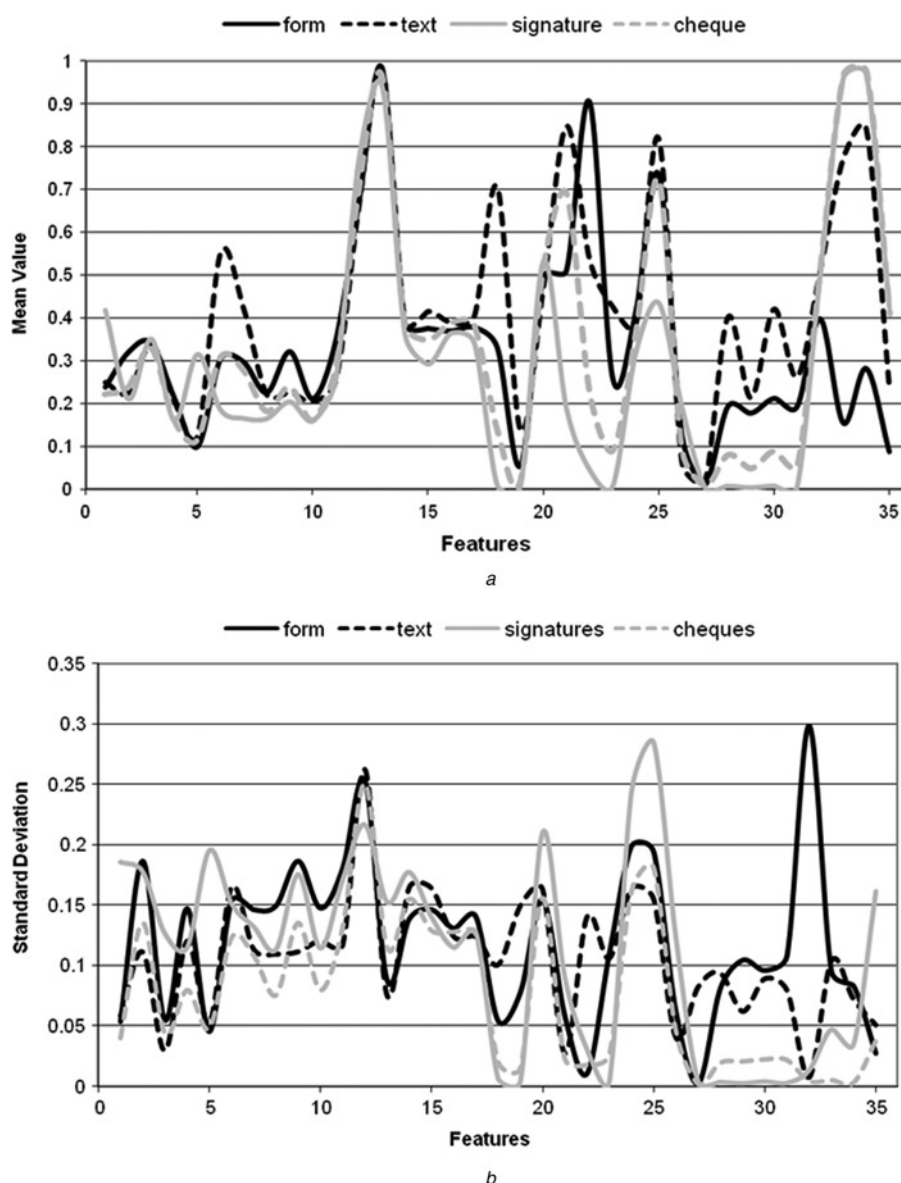
four different writing scenarios represented within the database.

Fig. 1 shows some very interesting feature variations according to the writing scenario being considered. It is useful to assess the features when divided into four broad subsets, namely velocity features, pen-pressure features, angular features and static shape features. One exemplar feature from each subset, demonstrating large similarities or differences, is discussed here. Fig. 2 shows the mean feature values for each subject and test scenario. The first exemplar feature is average horizontal velocity (Fig. 2a). Empirically, we have identified that all velocity features exhibit similar properties and therefore the displayed feature is representative of the entire velocity feature set.

From Fig. 2a, it can be seen that signing was performed with much greater speed than the other target writing tasks and therefore velocity can be a factor supporting discrimination between writing patterns within this task. Fig. 2b shows an example of a pen-pressure feature (maximum pen-pressure acceleration). It can be seen that the variation of the values for signatures is much greater than for the other scenarios, whereas the values representing the text writing scenario are typically the highest, showing the greater variations in pen pressure while writing a large amount of text, rather than creating a signature, which for many writers shows very low pen-pressure variation. The next class of features corresponds to angular features representing the pen position and pen rotation. These features show an interesting trend of non-variability across different writing scenarios. The example we consider here is altitude (Fig. 2c) relating to the angle of the pen body to the writing surface. This feature can be successfully used for establishing the authorship of a number of different types of documents and can be very useful in forensic practice, as well as for an automatic writer identification application. Finally, we consider a feature representing the subset of general static features, namely spread (Fig. 2d). We can see that the values for this feature across different writing patterns are distinctly different, with a large variation for signature patterns. The above four examples demonstrate how feature distributions vary according to the writing scenario being undertaken. Having shown these exemplar data, analysis of variance (ANOVA) is used to formally quantify these and other potentially more complex relationships.

ANOVA [32] is a statistical method for determining factors that produce variability in empirical observations. The hypothesis of no effect (null hypothesis) can be tested by assessing equality of several population means. The approach is to compare the means of sum of the squares that are in fact estimators of a common population variance. The comparison between the actual variations of the group averages is expressed in terms of





**Figure 1** Feature radiations

*a* Mean for different writing tasks

*b* Standard deviation curves for different writing tasks

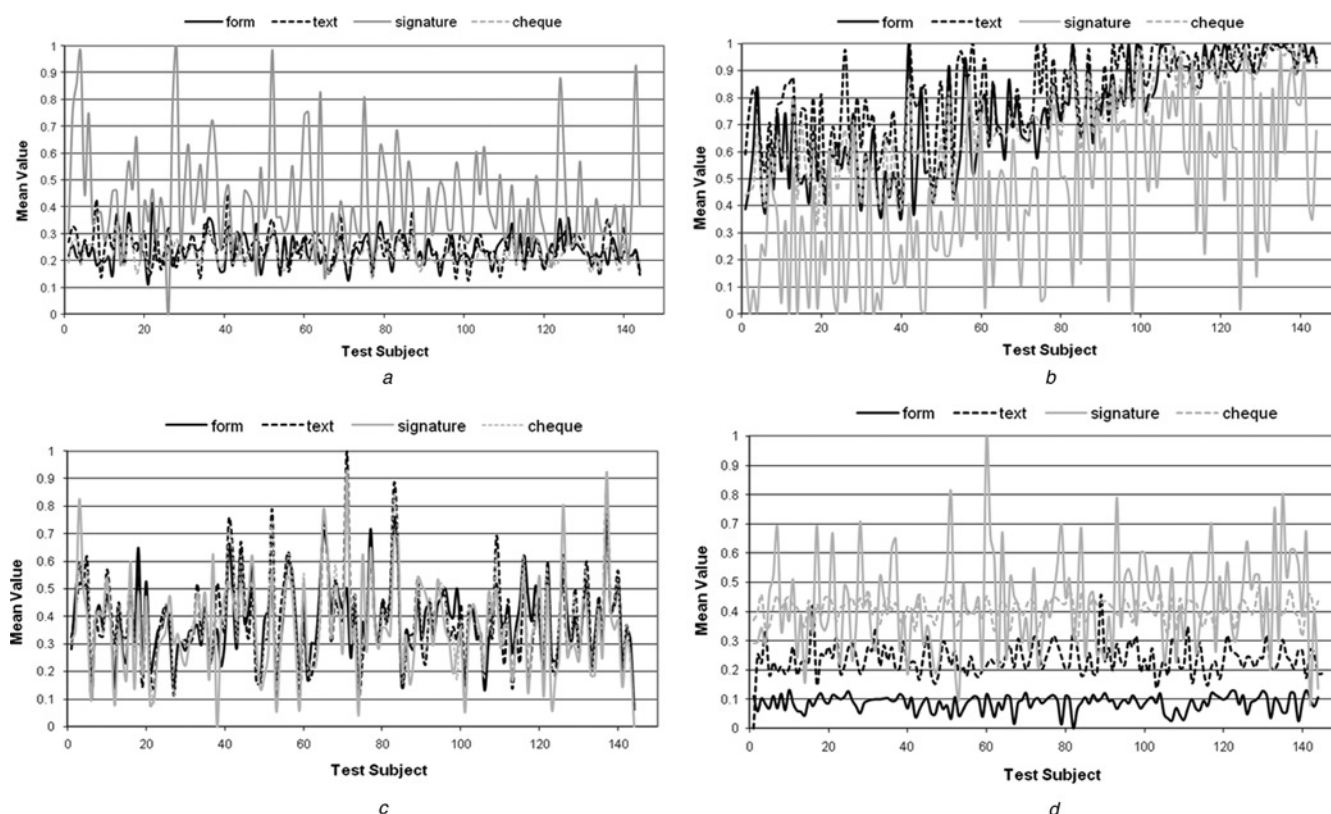
the  $F$  ratio

$$F = \frac{v_f}{v_E} \quad (2)$$

where  $v_f$  is a found (measured) variation of the group averages and  $v_E$  an expected variation of the group averages.

Thus, if the null hypothesis is correct,  $F$  is expected to have a value around 1, whereas a 'large'  $F$  indicates a localised population effect. In order to determine how large  $F$  should be allowed to become before the null hypothesis is rejected, it is necessary to compute the value of  $p$  (the significance level). A limitation of ANOVA is that it only detects significant differences among means, but does not

indicate the functional form of the relationship among the means. By analysing the variances of mean curves (Fig. 1*a*), it is shown that no significant differences were revealed between the four tasks when the entire set of features was used ( $F(3, 136) = 1.31, p < 0.27$ ). On the other hand, the curve representing the standard deviation (Fig. 1*b*) of these features exhibits significant differences between the four tasks, as shown by the analysis of variances ( $F(3, 136) = 2.67, p < 0.04$ ). However, by eliminating unrepresentative features from the feature set, it is possible to prove the hypothesis that a handwriting sample can be assigned to one of four task types with a high degree of confidence. For this purpose, let us initially consider the Euclidean distance measure between the four task-type curves shown in Fig. 1*a* for each feature individually. Following the application of this distance calculation,



**Figure 2** Feature distributions

- a Average horizontal velocity
- b Maximum pen-pressure acceleration
- c Average altitude
- d Spread

features are sorted in descending order, so that the features exhibiting largest differences are presented at the beginning of Table 3.

Fig. 3 shows the distances graphically, where it is possible to see that at the point corresponding to the 18th ranked feature, the curve starts to flatten out. The curve can therefore be divided into roughly three slope regions (feature ranks 1–5, 6–18, and 18–35).

Analysing the variances for the mean and standard deviation curves, based on the features described in Table 2, the plots shown in Fig. 4 are obtained. These represent the ANOVA significance levels,  $p$ , using an incremental number of features from 2 to 35 in the rank order shown in Table 2. The optimal number of features to be used to discriminate between different task types has been established to be the first 18 ranked features ( $F(3, 68) = 2.02$ ,  $p < 0.11$  for mean and  $F(3, 68) = 2.93$ ,  $p < 0.03$  for standard deviation).

### 3.2 Analysis of individual features

The above analysis was aimed at a combination of all 35 features within the feature pool. We now analyse each

feature separately according to personal writer demographics, with a view to determine which features contribute to the discrimination between specific characteristics such as gender, writer's age group and handedness. The variances of individual features are analysed and ANOVA tables constructed. Since the significant differences in signals occur when  $p < 0.01$ , Tables 4–6 represent a list of features where significant inter-group differences occur and hence can be used to discriminate between the selected demographic characteristics.

**3.2.1 Genuine data samples:** First, ANOVA was performed for feature vectors representing the genuine data samples taken from test subjects' first session. The results are shown in Table 4. The values relate to the feature IDs where the significance level from ANOVA analysis was shown to be  $p < 0.01$ .

The first row shows features which have been identified as being significantly different across the four writing scenarios under consideration. The first of these features are the maximum horizontal (feature ID 2) and maximum vertical velocities (feature ID 4) with features 8–11 also relating to the pen velocity. This shows that a writer performs

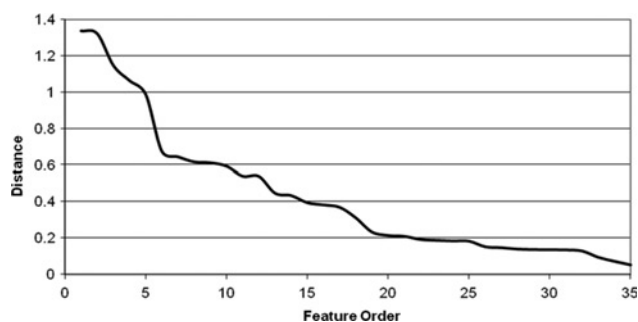
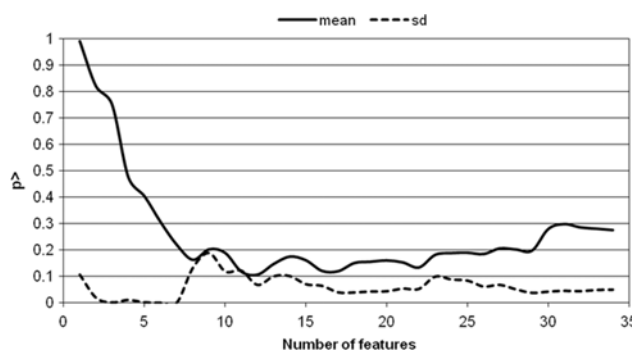
**Table 3** Between-task Euclidean distances sorted in descending order

Feature ID	Distance	Feature ID	Distance	Feature ID	Distance
F33	1.34	F31	0.47	F11	0.18
F22	1.22	F5	0.43	F3	0.15
F34	1.15	F1	0.39	F8	0.15
F18	1.06	F29	0.38	F27	0.14
F21	0.99	F7	0.37	F10	0.14
F23	0.67	F19	0.31	F4	0.14
F30	0.64	F26	0.23	F13	0.13
F28	0.62	F9	0.21	F20	0.13
F25	0.61	F2	0.21	F17	0.09
F35	0.59	F24	0.19	F14	0.07
F32	0.54	F15	0.19	F16	0.05
F6	0.54	F12	0.18		

different handwriting tasks with different pen velocities adopted during execution. Next, we can see the features related to pressure, specifically average pen pressure, maximum pen pressure and average pen pressure acceleration (ID 12, 13, 24, respectively). Finally, the last two features which contribute to target task discrimination are maximum azimuth and orientation (ID 17, 32). As can be seen from Table 4, no features were found for any of the writing tasks which could aid discrimination on the basis of writer gender. Rows 6–9 represent the analysis of feature vectors derived from six different age groups (18–30, 31–40, 41–50, 51–60, 61–70 and over 70). Here, we can observe many different features which show the possibility that a writer's age may be reflected in his/her handwriting as captured within the feature set defined. As can be seen, the best of the four target tasks for generation of information to support determination of the writer's age is the form-filling task. Here, velocity is a very strong discriminator (features 2, 6–9, 11). Other features that are useful in the determination of a writer's age are similar for all four target tasks. These features are pen pressure (12), number of pen-ups (18, for signature only), slant (20, form

only), writing duration (23), average and maximum pen-pressure acceleration (24, 25), and finally, positive and negative duration of horizontal and vertical velocities (28–31). Finally, rows 10–13 show the outcome of an analysis of feature vectors when participants write with their left and right hands, respectively. Not surprisingly, handedness is reflected in azimuth, acceleration (26, 27) and by orientation (32, for text only).

**3.2.2 Handwriting imitation tasks:** Table 5 presents the results of an ANOVA for the forged data (i.e. where a subject was asked to imitate the writing of another writer), collected during a test subject's second session. The database contains nine samples of forged signatures and three forged cheques for each of 140 participants (all apart from first 10, whose handwriting data were used as forgery targets). As only two scenarios were used in order to generate the forgery data (signature and cheque production – the most common scenarios for unskilled forgeries as opposed to form and text production which are typically skilled forgeries) only these data are considered. This part of our experimental study was restricted to these two scenarios on

**Figure 3** Feature distances**Figure 4** ANOVA *p* values



**Table 4** Significantly different features in genuine data samples

Factor	Scenario	Feature ID
all	all	2, 4, 8, 9, 10, 11, 12, 13, 15, 17, 24, 32
gender	form	-
	text	-
	signature	-
	cheque	-
age	form	2, 6, 7, 8, 9, 11, 12, 20, 23, 24, 25, 28–30
	text	5, 12, 23–25, 28–31
	signature	5, 12, 18, 23–25, 28–31
	cheque	3, 12, 23–25, 28–31
hand	form	27
	text	26, 27, 32
	signature	26, 27
	cheque	26, 27

the explicit advice of a practising forensic document examiner, on the basis that the vast majority of forgeries occur in signature or cheque scenarios.

Assessing [Table 5](#) shows that, when comparing signature and cheque tasks, features representing pen velocity characteristics (5–8), maximum altitude (15) and average azimuth acceleration (26) can contribute to the content discrimination. Very interestingly, for forged samples, gender seems to be related to average Cartesian velocity and maximum altitude (5, 15). The age of a forger, on the other hand, can be determined by Cartesian velocity (5), pen-pressure features (13, 25), and by writing duration features (23, 28–31). Finally, it is possible to assemble evidence about whether a forger is right or left handed by

**Table 5** Significantly different features in forged data samples

Factor	Scenario	Feature ID
all	all	5–8, 15, 26
gender	signature	5, 15
	cheque	5, 15
age	signature	5, 13, 23, 25, 28–31
	cheque	5, 23, 25, 29
hand	signature	19
	cheque	26

**Table 6** Significantly different features with respect to a writer's genuine and forged response

Factor	Scenario	Feature ID
All	signature	1, 7, 12, 13, 18, 21, 22, 24–26, 35
	cheque	6, 7, 12, 13, 18–20, 22, 25, 26, 31–33, 35
Gender		
male	signature	1, 5, 13, 18, 21, 23, 24, 26, 28–31
	signature	1, 5, 7, 12, 13, 18, 19, 21–26, 29–31
female	cheque	1, 5, 19, 23–26, 28–33, 35
	cheque	6, 7, 13, 18–20, 22, 24–26, 31, 35
Age		
18–29	signature	1, 5, 7, 12, 13, 18, 19, 21–24, 26, 29–31
	signature	1, 2, 5–7, 23, 26, 28–31
30–40	signature	26, 28, 30
	signature	1, 5, 20, 22–26, 28–31, 33–35
40–50	signature	1, 23, 24, 26, 28–31
	signature	1, 5, 22–26, 28–31, 35
50–60	signature	1, 5, 22–26, 28–31, 35
	signature	1, 6, 7, 12, 13, 19, 21–26, 28–32, 35
60–70	signature	1, 5, 23, 24, 26, 28–31
	signature	1, 5
over 70	signature	1, 5, 23, 24, 26, 28–31
	signature	1, 5, 19, 23, 24, 26, 28–31
18–29	cheque	1, 5, 19, 22–24, 26, 28, 30, 32, 35
	cheque	1, 5, 19, 22–24, 26, 28, 30, 32, 35
30–40	cheque	1, 5, 23, 24, 26, 28–31
	cheque	1, 5
40–50	cheque	1, 5, 23, 24, 26, 28–31
	cheque	1, 5, 23, 24, 26, 28–31
50–60	cheque	1, 5, 23, 24, 26, 28–31
	cheque	1, 5, 19, 23, 24, 26, 28–31
60–70	cheque	1, 5, 19, 23, 24, 26, 28–31
	cheque	1, 5, 19, 22–24, 26, 28, 30, 32, 35
over 70	cheque	1, 5, 19, 22–24, 26, 28, 30, 32, 35
	cheque	1, 5, 19, 22–24, 26, 28, 30, 32, 35
Hand		
left	signature	5, 21, 23, 24, 26, 28–31
	signature	1, 7, 12, 13, 18, 19, 21, 22, 24, 25, 35
right	signature	1, 7, 12, 13, 18, 19, 21, 22, 24, 25, 35
	signature	1, 5, 19, 23, 24, 26, 28–31
left	cheque	1, 5, 19, 23, 24, 26, 28–31
	cheque	1, 5, 19, 23, 24, 26, 28–31
right	cheque	1, 5, 19, 23, 24, 26, 28–31
	cheque	6, 7, 12, 13, 18–20, 22, 25, 31–33, 35

considering the pen-down to pen-up ratio (19) as well as average azimuth acceleration (26).

### 3.2.3 Genuine against forged data samples:

[Table 6](#) presents the results of a comparison between subjects' genuine and forged/copied data samples. The purpose here is to determine the features which exhibit significant variation when a subject is writing in his/her own writing style, or when (s)he is attempting to copy another individual's signature or handwriting.

Table 6 shows that a number of features support the process of distinguishing genuine writing from copied/forged writing. These differences are represented by velocities (mostly horizontal, IDs 1, 5–7), pen-pressures (12, 13, 24, 25), pen-ups (18, 19), handwriting shape and dimensions (21, 22, 32–35) and writing durations (23, 28–31) across different groups in the database population. Nevertheless, features representing altitude and azimuth (14–17, 27), which are connected closely to physical characteristics such as hand and arm configuration, do not show such significant differences and thus do not appear in this Table. From this, we can conclude that these features are generally stable for each writer, no matter if he/she is writing in his/her usual manner, or trying to copy another individual's writing. These features, therefore, can be effectively used for writer verification applications.

It is interesting to note when analysing Tables 4–6 that many of the features that show significant differences between writing scenarios and demographic groups are based on dynamic/constructional/timing aspects of production which highlights the importance of the inferred dynamics within conventional forensic analysis and the features that have been implemented as part of this study.

### 3.3 Static features

As we have already observed, almost all conventional forensic handwriting analyses are based on static information extracted from an examination of the end product of the writing process or, at best, information about dynamic characterisation which can be inferred from the static writing image [5, 6]. This is in sharp contrast to the automated analysis of handwriting generally deployed in, for example, commercial online document reading or biometric identification scenarios, where directly acquired dynamic information may often be most productively utilised [25]. It is of considerable interest, therefore to examine briefly the effectiveness specifically of the static features in our feature pool, in order to gain some insight into an aspect of handwriting analysis which is likely most sharply to point out differences in approach between the two complementary research communities.

In contrast, therefore, to our previous investigation of feature characteristics across the whole of our feature pool, here, we focus specifically on the static features within the pool. Examination of the static features within the data presented in Fig. 1 reveals that their values vary greatly depending on the writing scenarios, with the possible exception of slant (feature 20) and orientation (feature 32). Fig. 5 shows examples of mean feature values for all subjects in the database. We can see that slant is similar in different writing scenarios, whereas height and inertial ratio vary greatly.

Tables 4–6 represented the results obtained from ANOVA across the entire pool of features. Here, Table 7

represents a subset of the relevant data where only static features are analysed. In these results, when genuine data samples are analysed the only writing scenarios identified by ANOVA as containing features that significantly differ are the signature and cheque scenarios. When genuine data are analysed against forged data, only the form and text scenarios are found useful for identifying the respective information. Comparing this situation to the case for dynamic features, Table 7 shows relatively few entries, implying (perhaps unsurprisingly) that dynamic data increase the sensitivity to forgery detection. To identify gender by using static features, we can see that height and width for signatures and moment features for cheque were shown to have significant differences. Features shown to be

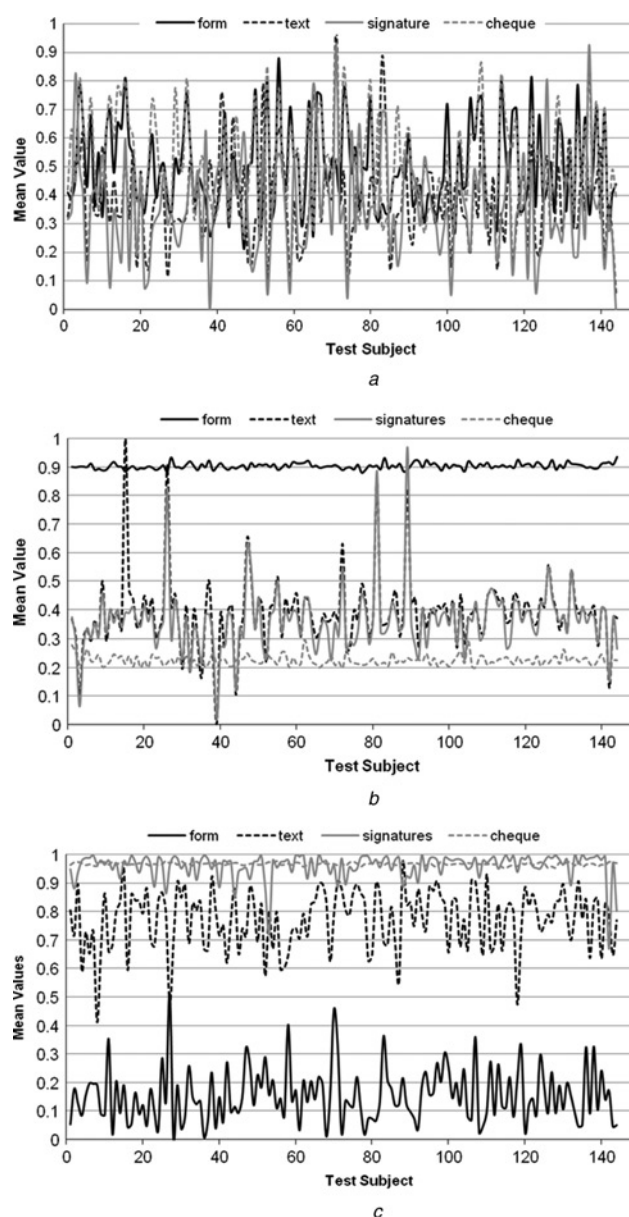


Figure 5 Static feature distributions

- a Slant
- b Height
- c Inertial ratio

significantly different across different age groups are height and spread for the signature and cheque scenarios. Handedness is shown to be identified by width and slant. When forged data are analysed, ANOVA did not identify any significant differences between static features across different populations represented in the given database. Finally, when a writer's genuine data are compared against the corresponding forged data, slant and orientation are the features that seem to be useful, although producing only three entries in the table.

Our analysis of static features has therefore shown that they are effective in the identification process only within a limited number of writing scenarios, confirming both the inherent limitations they embody and the advantages of introducing

dynamic features into analysis of handwriting where this can be achieved. This carries some potentially significant messages at the interface of forensic and engineering applications of handwriting analysis.

## 4 Summary

This paper analyses an extensive collection of genuine and forged writing produced by 150 writers, enabling us to investigate the process of creating forgeries and the relation of forgery activity with activity based on the forger's own handwriting. All writing samples were analysed with respect to 35 widely used features, and ANOVA results between writing tasks and writer demographics have been presented.

This initial analysis of data enables the identification of those features that remain stable when the writer is forging and which features can facilitate the discrimination between some of the writers' personal characteristics. Based on the type of handwriting task being undertaken, it is possible to establish how feature values vary and, therefore, how different writing scenarios can be considered separately to improve classification. The variation in features according to the sample being genuine or forged was established, with different tasks yielding different performance profiles. Additionally, we have investigated how a number of important demographic characteristics can be successfully classified based on the analysis undertaken.

This analysis provides us with important insights into the way in which writing task, writer characteristics, original/forgery execution patterns and feature types all interact in determining the extent to which writer identification can be achieved in practice. Perhaps equally important is the fact that the study reported here has begun to explore the boundaries between two traditional research communities where greater cross-over of ideas and techniques could be productively encouraged. A greater exploitation, where this can be achieved, of static handwriting analysis in the 'engineering' sector would undoubtedly have positive benefits, explicitly widening the range of applications which can be addressed. For example, the remote processing of handwritten documents (e.g. bank cheques) is case in point, where the nature of the offline data capture is inherent in the application characteristics. Indeed, there are many such instances (form-based tasks, travel documents etc.) where the nature of task and the capture conditions occur in different combinations. In such circumstances, exploiting the sort of 'intelligence' made available by this type of analysis can also contribute to better matching between task and processing platform in designing an optimal engineered solution. In the forensic analysis community, identifying opportunities where dynamic characteristics can be captured or reliably inferred will certainly open up significant new possibilities for improving the range of task domains which can be successfully studied and the level of success which can be achieved.

**Table 7** Significantly different static features according to top scenario and demographic

Factor	Scenario	Feature ID
Genuine data samples		
All	signature	21, 22, 35
	cheque	20, 22, 32, 33, 35
Gender		
male	signature	21
	cheque	21, 22
female	signature	21, 22
	cheque	32, 33, 35
male	signature	21, 22
	cheque	20, 22, 35
Age		
18–29	signature	21, 22
	cheque	20, 22, 33, 34, 35
50–60	signature	22, 35
	cheque	21, 22, 32, 35
over 70	signature	22, 35
	cheque	22, 32, 35
Hand		
left	signature	21
	cheque	21, 22, 35
right	signature	21, 22, 35
	cheque	20, 22, 32, 33, 35
Forged data samples		
	none	
Genuine against forged data samples		
all	all	32
	form	20
age	text	32
	hand	

## 5 Acknowledgment

The authors gratefully acknowledge the support of EPSRC and Document Evidence Ltd. for this work.

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